TUMOUR DETECTION IN BRAIN AND PANCREAS USING SOFT COMPUTING TECHNIQUES

A SYNOPSIS

Submitted by

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(Reg. No. 201611117)

in partial fulfilment for the award of the degree

of

DOCTOR OF PHILOSOPHY

DEPARTMENT OF INSTRUMENTATION AND CONTROL ENGINEERING

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TAMILNADU, INDIA.

JUNE 2022

1. INTRODUCTION

The brain is one of the biggest and most complicated organs in the human body. Over 100 billion nerve fibres make up its structure, and billions of synapses transmit information between them. The tissue layer known as the meninges surrounds the brain, as given by Park et al. [1]. The skull protects the brain from injury or damage. Soft tissues like Cerebrospinal Fluid (CSF), White Matter (WM), and Gray Matter (GM) make up its structure (GM). One in every six persons worldwide suffer from brain syndrome, which includes a wide spectrum of illnesses and conditions including a brain assault, Alzheimer's, multiple sclerosis, seizures, intracranial damage, and many more. Over 400 neurological disorders are included in the National Institute of Neurological Disorders and Stroke's database.

Treatment strategies differ greatly between malignant pancreatic tumours, such as those in pancreatic cancer and neuroendocrine, and benign tumors, such as those observed in autoimmune or tumor-forming pancreatitis. Therefore, differential diagnosis of these tumors is important for the appropriate selection of treatment. Cross-sectional imaging studies, including computed tomography (CT) and magnetic resonance imaging (MRI), are widely used for the detection and differentiation of pancreatic tumors and are reported to have relatively high diagnostic capabilities for determining malignancy, as shown by Barat et al. [2]. However, false positive results on these cross-sectional imaging studies can be a problem.

In 2020, cancer will be the primary cause of death for around 10 million people globally. The most often afflicted organs by cancer are likely the brain, pancreas, breast, small intestine, prostate, and rectum, described Achard et al. [3]. About one-third of cancer fatalities are attributed to long-term cigarette and alcohol use, a high BMI, a diet lacking in fresh fruits and vegetables, and a lack of exercise. Roughly 30% of all cancers are caused by infectious diseases, such as the disease and the human papilloma virus (HPV). If cancer is detected early and correctly diagnosed, many different forms of cancer can be effectively treated. Any number of illnesses that can affect any region of the body are included under the broad term "cancer."

Cancer is defined as the uncontrollable expansion of malignant cells over their normal limits, which might then try to invade nearby body sections and cause tissue damage; this latter process is known as metastasis.

Typically, a brain tumour is identified via a neurological examination, brain imaging, and a sample. Numerous assessments of nerve function, such as those for balance, hearing, vision, and response speeds, may be included of the neurological exam. Imaging techniques including computed tomography (CT), magnetic resonance imaging (MRI), magnetic resonance angiogram (MRA), or X-rays are utilised to identify the tumour, pinpoint its location, and/or measure brain functioning activity. Clinicians will evaluate the tumour and make their intended diagnosis based on other observations if they are unable to safely collect and analyse tissue samples, such as biopsy. In the event that a biopsy is possible, a doctor can utilise it to determine the tumour grade and search for biomarkers that might help tailor the treatment approach. Brain tumours can be treated with surgery, radiation, and chemotherapy.

Image segmentation is the process of separating multiple parts from a digital image. The main goal is to further optimize the segmentation process so that it shows effective outcomes and is simple to understand. This technique is mostly used to locate objects and outline images, as given by Shehab et al. [4]. As a result, MRI is used to investigate the anatomy of the brain and pancreas (Magnetic Resonance Imaging). It has no effect on the body because it remains negated when exposed to radiation. It operates by combining radio waves with a magnetic field. Since then, there is a pressing requirement to segment a medical image with specific characteristics such as accuracy, speed of calculation, and robust segmentation results as well as consumer engagement, as shown by Liu et al. [5].

1. LITERATURE REVIEW

Here are represented the results and evaluations of a few recent, outstanding studies. Recent suggestions for segmentation challenges include neural networks (NN), support vector machines (SVM), and others, given by Pernas et al. [6]. Furthermore, a large body of research shows that the correctness of the right characteristics determines how reliable categorization jobs are. The effectiveness of several segmentation methodologies based on various feature extraction and selection methods, clustering techniques, and classifiers is analyzed in this paper.

Convolutional neural networks (CNNs) are used for classification and support vector machines (SVMs) are used to extract the features in Eser et al. [7].

Segmentation approach for tumour identification. To segment noisy 3D MR images, Nabanita and Kanta [8] suggested a globally reduced and spatially limited likelihood-based FCM method based on local entropies. Using deep learning training in a convolutional neural network classifier, Talo et al. [9] .'s technique was developed for segmenting the tumour and non-tumor fractions on T2-weighted brain MR images. In order to differentiate and define the atherosclerotic properties of diseased carotid arteries in brain pictures from healthy images, Bento et al. [10] constructed a machine learning system utilising the SVM classifier. Mesut et al. [11] presented a tumor segmentation method named Brain MRNet using CNN and hyper column techniques for feature extraction. This method provided better results even when augmentation techniques were not used, and it was more effective compared to other models.

To extract malignancy and edoema sections from the multimodal images of the BraTS 2018 and 2020 dataset, Kronberg et al. [12] developed a successful technique. The dice value and accuracy are compared to conventional approaches to see how effective the algorithm is. Liu et al. [13] developed a Scale adaptable Super feature-based MetricUNet classification approach to distinguish between tumour and non-tumor regions in brain MRI.

Fan et al. [14] created a unique network architecture for liver and tumor segmentation based on improved Ma-net.They incorporated a self-attention technique into the image segmentation technique. The self-attention method in particular to capture the spatial and channel relationships of feature maps is applied, as well as include Multi-scale semantic information depending on the channel relationships of any feature maps.

Weng et al. [15] preserve spatial information, INet extends the receptive fields by gradually increasing the kernel sizes of Conv-layers. INet additionally improves the training process by providing various shortcuts and fusing multilevel semantics by recombining the feature maps of all preceding layers.

Qu et al. [16] The core premise given in to use an improved image segmentation processing technique relying on extracted feature points from remote sensing pictures to ensure that the generated image segments preserve the most data for small-scaled objects after scaling.

Xia et al. [17] proposes using three visible spectral channels to identify high resolution cloud and cloud shadow using a Global Attention Feature Fusion Residual Network. The core of this network is ResNet, which is used to retrieve semantic information at various levels. Barat et al. [18] These simple jobs may work for lung nodule detection, but there are other characteristics that the DL algorithm should recognize in the unique area of pancreatic tumor, such as parenchymal atrophy or pancreatic duct enlargement, as described.

Ibrahim et al. [19] The findings given in show that the new technique outperforms the original SSA algorithm for the segmentation issue significantly. Experiments using the Mastology Research with Infrared Image dataset reveal that the proposed strategy is robust for segmenting various healthy and unhealthy instances images (DMR-IR). The search-zone limiting of the anomalies of the breast makes breast region extraction beneficial. In Zebari et al. [20], a novel centeredness, known as polar centeredness, and a novel loss function are also presented. This surpasses a group of state-of-the-art deep learning approaches by introducing the polar representation and FOCS architecture. Interestingly, only a small number of them focused on nucleus segmentation.

Xiao et al. [21] Meanwhile, the given techniques may not be suitable for capturing the properties of LUAD images if used directly. For instance, in the literature, image segmentation approaches usually developed their analytical solutions in Cartesian coordinates, which limits their ability to represent specific scenarios. To date, no previous work has given enough thought to this issue in the context of a polar coordinate system. Problems encountered with the above segmentation algorithms include (i) strong perception of noise (ii) higher processing time; (iii) lower accuracy in noisy images (iv) less accuracy segmentation and (v) lower accuracy of classification

MR scans of the brain and pancreas are mostly used for tumour categorization. By eliminating unimportant elements from the full image, it enables researchers and physicians to concentrate on the important features of a slide image without having to do tedious work. On the other hand, segmentation of MR images is crucial in a tumor-free environment. Filtering, feature extraction, and segmentation of the entire collection of data will be helpful for different types of algorithms.

To be more precise, it has long been acknowledged that the training samples used have a significant influence on how algorithms are implemented. Numerous studies that looked at picture segmentation had already been conducted and had shown promising findings.

There is a significant drop in spatial information obtained, resulting in convolutions in medical data and decreased efficiency. As a result, the proposed model is applied, which includes a variety of approaches for filtering and classifying the image, making it a more effective approach for digital signal processing and higher computational applications. Hence the proposed work focuses on developing an efficient system for Brain and Pancreatic tumor identification by initial filtering using Modified Decision Based Coupled Windows Median Filter (MDBCWMF). Filtered images are then subject to segmentation using an altered distance metric of the Fuzzy algorithm, extracting features with GLCM and later classified using through Dynamic Score Level Integration (DSLI). This improves the accuracy and are able to adapt to maximal scenarios of brain and pancreatic tumor detection.

2. RESEARCH PROBLEM

Brain and Pancreatic tumours may both be diagnosed in part with the use of MRI and CT scans; however, if the tumour is engulfed in edoema during the scan, radiologists may find it difficult to define its precise position since it is hidden by voluminous tissues and edemas. Even segments of healthy tissue cannot be separated using a basic image analysis technique used in imaging centres. In these circumstances, diagnosis will take longer, and the patient's chance of survival will drop if the surgery is aggressive. Additionally, the radiologist's task has been more unpredictable as the amount of data that has to be recognised grows. As a result, in all MRI sequences, the tumour, tissue, and must be completely demarcated automatically.

To assess the severity of the problem and strategize for the patient's diagnosis and treatment in the case of a benign or malignant tumour, more than two clinicians are needed. As a result, computation or assessment time must be drastically reduced, which can only be done by using fewer manual interventions. The entire life-saving procedure may be rendered useless by errors made in the detection of malignant tissues

or areas. Potential solutions to the aforementioned problems have been provided by this research study through the creation of intelligent hybrid for Filtering, segmentation, and classification approaches. The challenge requires for cautious and rapid analysis.

3. OBJECTIVE

The main objectives of the research are as follows:

I. To detect the tumor in Brain and Pancreas MR images using Fuzzy C means (FCM) clustering approach and Modified Distance Metric of FCM.
II. To analyse the segmentation accuracy Modified Distance Metric of FCM to segment the tumor and non-tumor portions in MRI in Brain and Pancreases.
III. To extract features with GLCM and later classified using through Dynamic Score Level Integration (DSLI). This improves the accuracy and are able to adapt to maximal scenarios of brain and pancreatic tumor detection.

4. CONTRIBUTIONS

5.1 Brain and Pancreatic Tumor Classification Based on GLCM k-NN Approaches Algorithm

The proposed k-NN classifier composes of the three stages, namely, (a) Median filtering model for image pre-processing (b) Fuzzy C-segmentation model for accurate segmented image and (c) Gray Level Co-occurrence Matrix (GLCM) for selecting relevant features. The refined features are then given as input to k-NN classifier. The segmentation outcomes of brain and pancreas images are given in Figure 1.

Precision, accuracy, specificity and recall are important parameters to be considered for evaluating the performance of the proposed system. The determination of k value clearly emancipates the classes. Experimental computation is done using metrics like precision, accuracy, specificity, and recall. in Table 1.

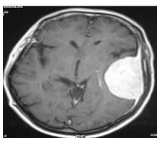
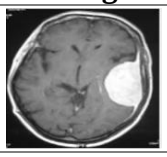
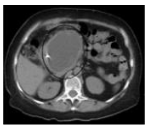
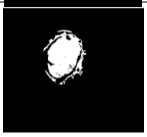
Organs	Input Image	Median filtering	FCM
A. Brain			
B.Pancreases			

Figure 1. Segmentation outcomes of Brain and pancreases images

Table 1. GLCM features extraction values

Classifiers	Images	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)
Proposed k-NN classifier	Brain MRI image	95.3	94.87	92.5	94.5
	Pancreatic CT Image	94.6	92.1	87.5	90
Support Vector Machines (SVM)	Brain MRI image	90.3	95.1	91.6	92
	Pancreatic CT Image	84.5	91.5	90	89.87
Naïve Bayes	Brain MRI image	90	94.3	90.5	91.6
	Pancreatic CT Image	84	90.2	89.5	88.5
Probability Neural Networks (PNN)	Brain MRI image	88.87	92	89.1	90
	Pancreatic CT Image	83.3	89.87	88.3	87.5

5.2 Brain and Pancreatic tumor segmentation using SRM and BPNN classification

The proposed method for performance measures attained from the proposed method is exemplified DBCWMF (Decision Based Coupled Windows Median Filter) to get better the image in means that enhance the possibility used for the accomplishment of the further progress. DBCWMF works effectively in the pre-processing compared to Median and PGPD filter in Segmentation Process Statistical region merging (SRM) algorithm to separate the input image into its constituent entities. With hybrid Feature extraction SIFT to convert the input data to a form appropriate meant for computer dealing out and CSO extracts the features results in some quantitative data that are basic make a distinction between one class of objects into another. Final with BPNN assigns the tag to an entity depends on the data offered

through its descriptors. The filtering, segmented and feature extracted outcomes of brain MR images are given in Figure 2.

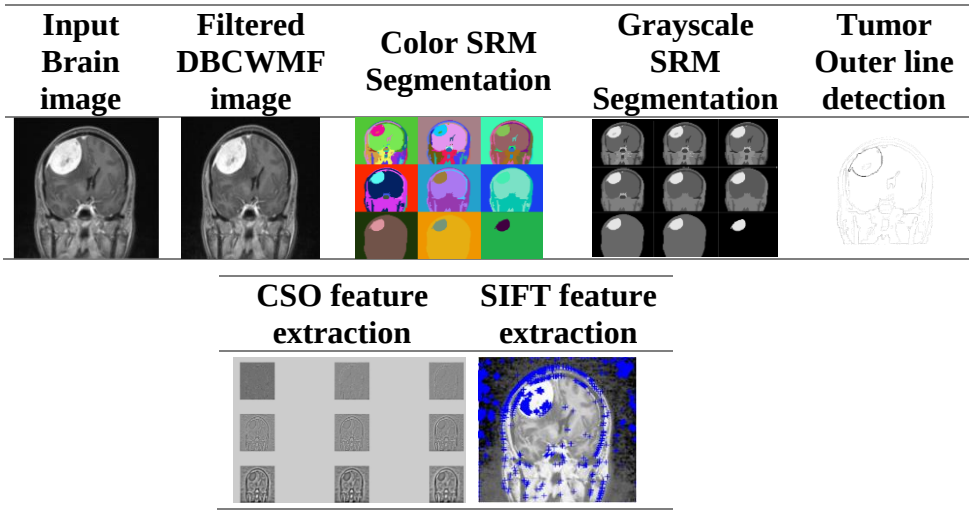


Figure 2. Filtering, Segmentation and feature extraction outcomes of Brain MRI.

The filtering, segmented and feature extracted outcomes of pancreas CT images are given in Figure 3.

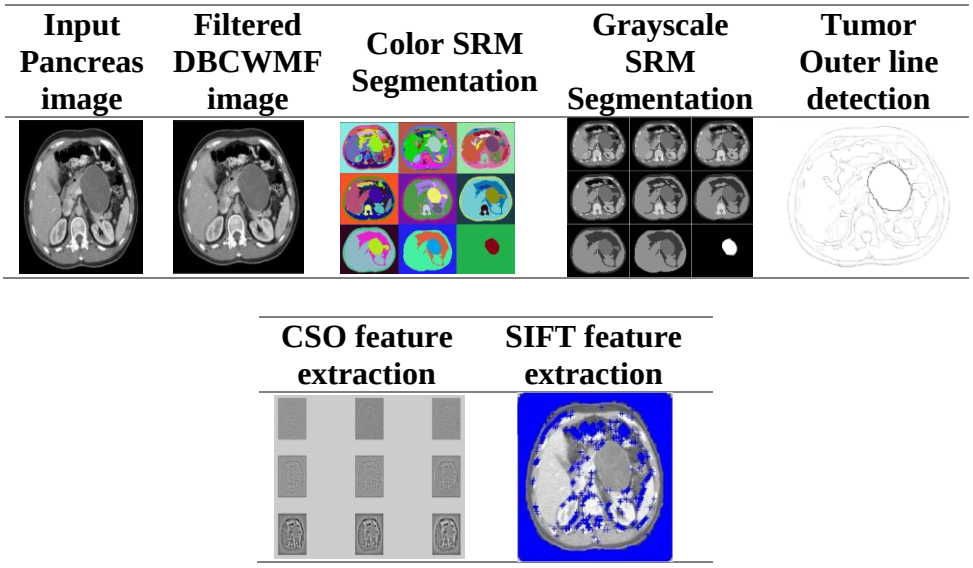


Figure 3. Filtering, Segmentation and feature extraction outcomes of Pancreas CT images.

The performance measures of brain, such as MSE, PSNR, SSIM and NCC have been given in Table 2.

Table 2. Performance measures of Brain

Parameters	MSE	PSNR	SSIM	NCC
MEDIAN	258.90	23.12	0.6234	1
PGPD	188.63	25.24	0.7256	1
DBCWMF	103.49	27.76	0.9167	1

The performance measures of pancreas CT images have been given in Table 3.

Table 3. Performance measures of Pancreas

Parameters	MSE	PSNR	SSIM	NCC
MEDIAN	188.88	25.12	0.7222	1
PGPD	143.56	26.24	0.8112	1
DBCMF	84.29	28.86	0.9234	1

The performance measures of brain and pancreas images, according to their accuracy, precision, specificity and recall parameters have been given in Table 4.

Table 4. Performance measures of Brain and Pancreas

Parameters	Brain	Pancreatic
Accuracy	95.56%	90.2 %
Precision	99.45%	92.86 %
Specificity	99.46%	93.34 %
Recall	92.34%	86.67 %

5.3 Spotting Brain and Pancreatic Tumor identification through SRM segmentation and Naive Bayes

The proposed method includes the Filtering the medical image histogram equation, SRM, GLCM and naive bayes for classification. Which involved Medical scanned image input which Pre-processing as DBCWMF image in filter and histogram equation for getting enhanced image and here Segmentation was carried out with Statistical region merging (SRM) Feature are extraction by GLCM and finally Classification done with Naive bayes of accuracy. In order to distinguish between one classes of objects from another, hybrid feature extraction uses SIFT to transform the input data into a format suitable for computer use and CSO to extract the features. Using BPNN, a tag is finally assigned to an entity based on the information provided by its descriptors. The filtering, histogram, segmentation and feature extraction outcomes of brain MRI is given in Figure 4.

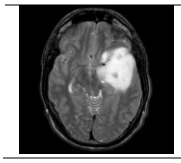
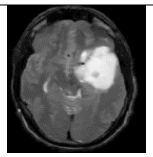
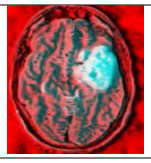
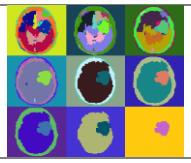
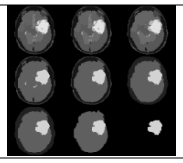
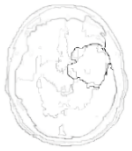
Brain input Image	Pre-processing image	Histogram output	Color SRM Segmentation	Grayscale SRM Segmentation	Tumor Outer line detection
					

Figure 4. Filtering, histogram, Segmentation and feature extraction outcomes of Brain MRI.

The filtering, histogram, segmented and feature extracted outcomes of pancreas images is given in Figure 5.

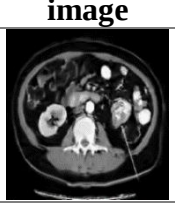
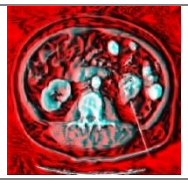
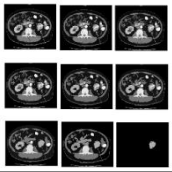
Pancreas input Image	Pre-processing image	Histogram output	Color SRM Segmentation	Grayscale SRM Segmentation	Tumor Outer line detection
					

Figure 5. Filtering, histogram, Segmentation and feature extraction outcomes of Pancreas.

The parameters measuring of brain and pancreas has been given in Table 5.

Table 5. Parameters measuring of Brain and Pancreas

Parameters	Brain	Pancreas
Accuracy	92.45 %	88.42 %
Precision	96.48%	90.11 %
Specificity	96.34 %	91.02 %
Recall	90.43 %	83.15 %

5.4 Spotting brain and pancreatic tumor using Fuzzy C-mean segmentation and SIFT extraction through sparse representation approach

The proposed method involves the Decision Based Couple Window Median Filter, histogram equation, Fuzzy C-segmentation SIFT extraction and classification with Sparse representation here MR image and CT scanned medical image input. The Pre-processing DBCWMF image in filter and histogram equation gives accurate results in terms of filtering and enhanced the image Segmentation Fuzzy C-

segmentation with identifying tumor region where as Feature extracted with SIFT extraction and Classification Sparse representation is use for testing of accuracy. The filtering, segmented and feature extracted outcomes of brain MR images is given in Figure 6.

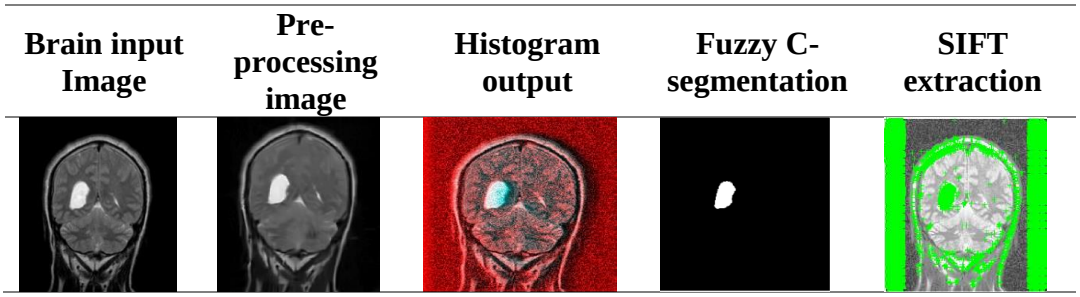


Figure 6. Filtering, histogram, Segmentation and feature extraction outcomes of Brain MRI.

The filtering, segmented and feature extracted outcomes of pancreas images is given in Figure 7.

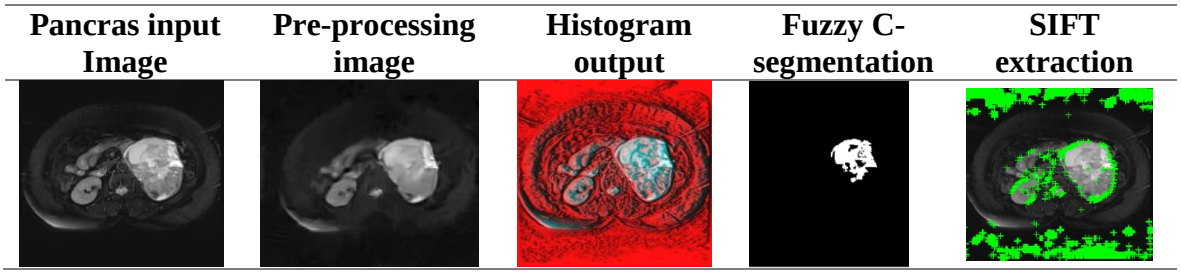


Figure 7. Filtering, histogram, Segmentation and feature extraction outcomes of Pancreas images.

The accuracy analysis for brain using different models are given in Table 6.

Table 6. Accuracy Analysis with different models-Brain

Parameters	**Probability neural networks (PNN)**	**ANN**	**Sparse Representation**
Accuracy	83.33 %	82.24	93.67 %

To be more exact, it has long been understood that how algorithms are implemented is significantly influenced by the training samples that are utilised. The results of several research that examined image segmentation so far have been encouraging. The accuracy analysis of pancreas using different models are shown in Table 7.

Table 7. Accuracy Analysis with different models- Pancreas

Parameters	**Probability neural networks (PNN)**	**ANN**	**Sparse Representation**
Accuracy	80.33 %	82.24%	91.21 %

5.5 Distance metric-based segmentation and score level classification for optimized tumor identification in MR images.

The phases of work for the suggested methodology are as follows: The brain and pancreatic MR images are acquired first. The Modified DBCWM Filter is used for pre-processing. After that, the filtered image is segmented using FCM's Modified Distance Metric. Following the segmentation process, the GLCM is used to extract features. Finally, the BNN and SR algorithms, as well as Dynamic Score Level Integration, are used to classify the data.

There is a major reduction in the spatial information acquired that causes convolutions among the medical data, leading to less efficiency. Hence the proposed model is used that consists of numerous methodologies for filtering and classifying the image that makes it a more effective approach for digital signal processing and higher computational applications. This method results in a lower segmentation error. The image is then feature extracted using a Gray-Level Co-Occurrence Matrix (GLCM) algorithm and classified using a parameterized combination of Back Propagation Neural Network (BPNN) and Sparse Representation (SR) approaches known as Dynamic Score Level Integration (DSLI).When compared to other state-of-the-art methodologies, MDM-FCM segmented yields good accuracy in classification yields good accuracy for brain and pancreas images, experimental valuation being done with Datasets from TCIA and Madurai Scan center. The input and output on brain image is shown in Figure 8.

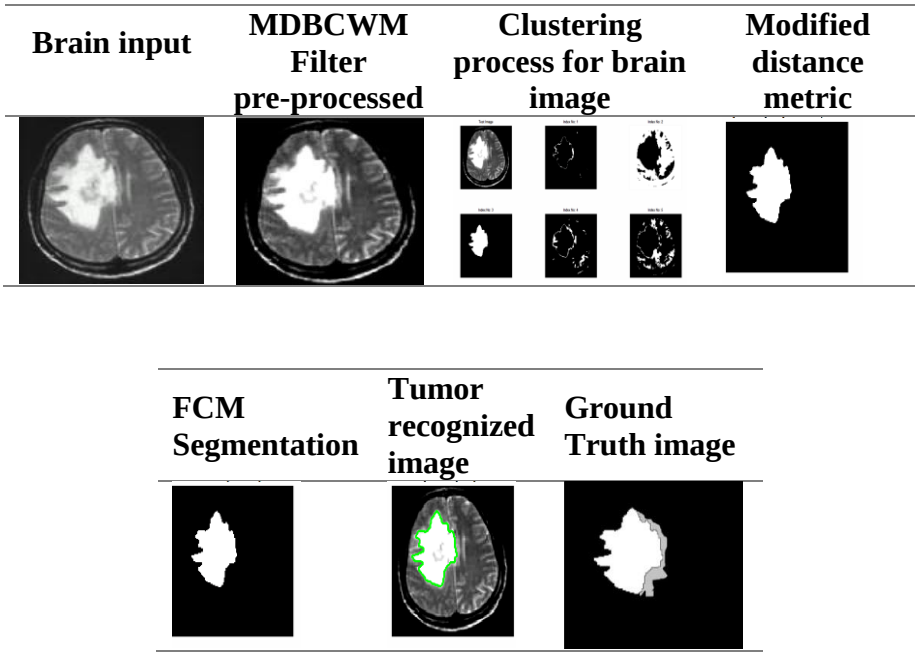


Figure 8. Input and output on brain image.

The input and output of pancreas images is given in Figure 9.

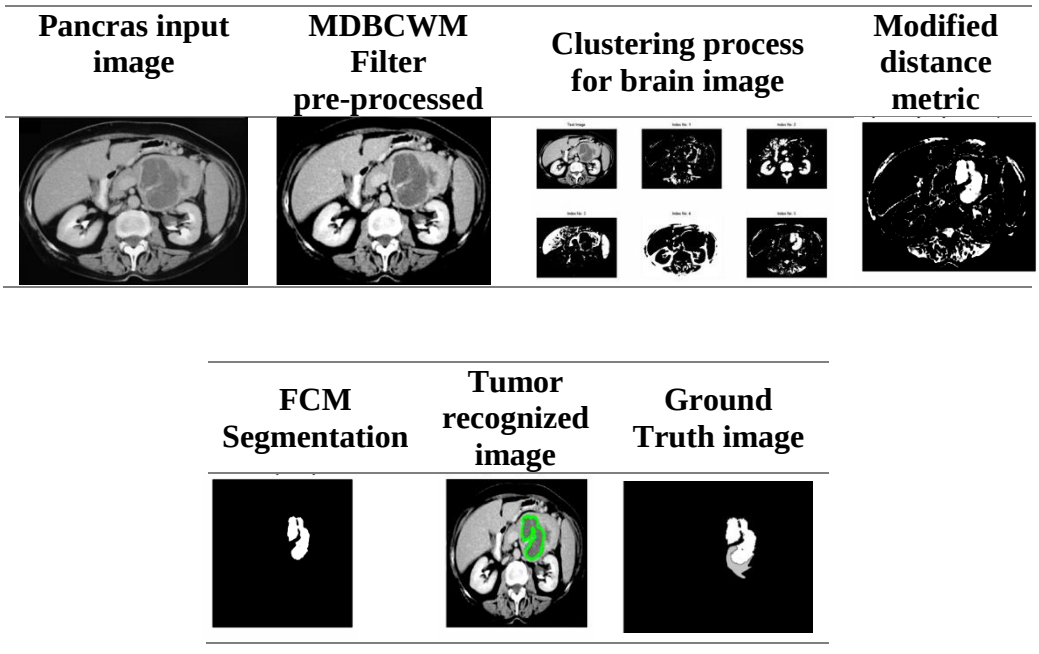


Figure 9. Input and output on Pancreas image.

The MDM-FCM proposed method yields higher sensitivity, specificity and similarity index than the other conventional segmentation algorithms like K-means and normal FCM. The segmentation comparison with modified FCM is shown in Table 8.

Table 8. Segmentation comparison with modified FCM – Brain

Algorithms (Brain)	Similarity index (SI)	Sensitivity	Specificity
K-means algorithm	0.7211	0.8162	0.8343
FCM	0.7464	0.9251	0.9437
Proposed MDM-FCM	0.8021	0.9767	0.9674

The different models accuracy analysis average with higher value for brain images is shown in Table 9.

Table 9. Different models Accuracy analysis average with higher value – Brain images

Parameters (Brain)	ANN	Adaboost	Naïve Bayes	RF	PNN	BPNN	SR	Proposed (Score level integration)
Accuracy (%)	90.21	91.12	92.46	92.26	85.61	93.67	92.54	97.84
Precision (%)	88.62	89.73	90.12	90.16	83.47	91.56	91.22	96.44
Sensitivity (%)	90.71	90.76	92.82	92.48	85.81	93.92	93.78	98.11
Specificity (%)	89.86	90.63	92.08	92.02	85.04	93.25	92.23	97.24

The different models accuracy analysis average with higher value for pancreatic tumor images is given in Table 10.

Table 10. Different models Accuracy analysis average with higher value – Pancreatic images

Parameters (Pancreas)	ANN	LSSVM	SR	Naïve Bayes	Proposed (Score level integration)
Accuracy (%)	96.67	91.67	89.21	90.42	95.62
Sensitivity (%)	97.3	89.66	91.32	90.44	96.02
Specificity (%)	95.65	94.74	91.26	91.02	95.03

5. ORGANIZATION OF THE THESIS

The structure of this thesis is organized into eight chapters, as follows:

Chapter 1

This chapter provides an explanation of the significant identification of brain and pancreatic tumors MR and CT image segmentation in the diagnosis of those abnormalities. The research problem discussed and the motivation behind choosing brain and pancreas as a subject for this work is also represented in this section.

Chapter 2

This chapter provides an overview of the many studies that have been conducted by researchers on pancreatic and brain cancers. The reasoning for the suggested structure has also been described here using various techniques and methodologies.

Chapter 3

This chapter talks about developing an automatic recognition methodology for brain and pancreas images with precise segmentation and classification process. Median filtering model was used as pre-processing model, GLCM for selecting relevant features and k-NN as a classification model.

Chapter 4

This chapter encapsulates the detection of brain and pancreatic tumor by using a Decision based Couple Window Median Filter as a pre-processing method. SRM is used for segmentation, with Scale-invariant method and Cat swarm optimization being used in a hybrid manner for feature extraction. The classification process is carried out using BPNN approach.

Chapter 5

This chapter does a comparison analysis of various segmentation, feature extraction and classification approaches. During this process, the work has been divided into two categories: i) using the previous DBCWMF pre-processing approach with histogram equalization, SRM used as a segmented, the features are extracted

using GLCM process, and finally classified using a Naïve bayes classifier; ii) a different analysis is done here using similar pre-processing approach, Fuzzy-C being used as a segmented. Here SIFT is used for feature extraction, and a novel Sparse Representation algorithm is employed for classifying. By comparing the above methodologies, the results yielded showed the efficiency of algorithms such as DBCWMF, GLCM and SR.

Chapter 6

This chapter reports on the investigation of MR brain and pancreas images for efficient segmentation and classification process. A Modified DBCWMF approach is used for pre-processing, whereas the segmentation is carried out using a Distance based modified version of the conventional Fuzzy-C algorithm. The conventional BPNN and SR classifiers are combined to form a composite classification algorithm termed as Dynamic Score Level Integration classifier.

Chapter 7

This chapter draws a conclusion to the thesis, and also discusses the future work to be carried out in this context.

6. CONCLUSION

This work focuses on identifying tumor in brain and pancreas images using several soft computing techniques. The best algorithm for filtering DBCWMF is used to de-noise (filter or pre-process) the input brain or pancreas MR as well as CT images. The images are then segmented using the distance metric modified FCM approach. The feature extraction method is done with a GLCM approach, while the classification procedure is done with Dynamic Score Level Integration, which is a combination of BPNN and SR approaches. The research work concludes with the revelation of considerable recommendation for future investigation. The references of all the hybrid algorithms that are employed for the filtering, segmentation and classification of MR brain and pancreas images in this research work are enlisted. The classification throughout attained higher performances. In the future, this computer-assisted method could be utilized to classify images with a variety of clinical disorders, types, and illness states.

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LIST OF PUBLICATIONS

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